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AN ANALYSIS OF THE INFORMATION CONTENT OF ALTERNATIVE CREDIT AGGREGATES

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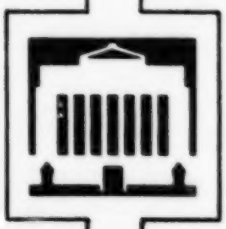

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by
Leslie Milton

The views expressed in this study are those of the author, and no responsibility for them should be attributed to the Bank of Canada.

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ABSTRACT

This study evaluates the information content of twenty-five measures of credit with respect to three macroeconomic variables - nominal spending, real spending and prices. Initially, simple descriptive techniques are used to assess the contemporaneous and leading relationships between the credit aggregates and the three goal variables. Next, bivariate vector autoregression models are constructed by regressing each of the goal variables on its own past values, then adding contemporaneous and lagged values of the credit aggregates. Multivariate models are developed by introducing other financial variables (which include an interest rate, an exchange rate and a stock market price index) into the simple bivariate equations as explanatory variables. The models using different measures of credit are compared with one another and with models using various monetary aggregates. It is found that while individual monetary aggregates are more informative than measures of credit, the latter may have a valuable complementary role to play as macroeconomic indicators.

RÉSUMÉ

Dans cette étude, on procède à l'analyse du contenu informatif de vingt-cinq mesures de crédit dans le but de cerner les relations qui existent entre celles-ci et trois variables macroéconomiques - la dépense nominale, la dépense réelle et les prix. On a d'abord évalué, à l'aide de techniques descriptives simples, la simultanéité de ces relations ou l'antériorité du crédit par rapport aux trois variables. Puis on a construit des modèles autorégressifs vectoriels à deux variables et opéré la régression de chacune des variables cibles par rapport à leurs valeurs passées et aux valeurs instantanées et retardées de mesures du crédit. On a ensuite procédé à l'élaboration de modèles à plusieurs variables en introduisant dans les équations simples à deux variables d'autres variables financières - tels le taux d'intérêt, le taux de change et un indice des cours bousiers - à titre de variables explicatives. On a effectué une analyse comparative des modèles où interviennent différentes mesures du crédit et ceux-ci sont ensuite confrontés avec les modèles intégrant divers agrégats monétaires. Il est démontré que, même si ces agrégats ont un contenu informatif plus large que les mesures de crédit, ces dernières peuvent jouer un rôle complémentaire important comme indicateurs macroéconomiques.

1 INTRODUCTION

Over the past two decades, numerous studies have investigated the information content of monetary aggregates in the quest for macroeconomic indicators. The examination of credit aggregates has been much more modest. Since there are no obvious reasons for presuming that financial aggregates which comprise the liabilities rather than the assets of financial intermediaries are superior macroeconomic indicators, it is clear that a gap exists in our information content research. This study seeks to rectify the imbalance in our knowledge of the indicator properties of credit and monetary aggregates.

While theory suggests that the long-run effects of movements in money and credit are identical, there is no clear indication of which of these two markets will provide us with the best short-run information. If one delves into the credit literature, complex models yield scenarios in which assets of financial institutions (credit) play a dominant and active short-run role in macroeconomic adjustment. While no attempt is made here to review this literature, we refer to the models of Brunner and Meltzer (1976), to the buffer stock theory popularized by Laidler (1984, 1985) and to the models of Modigliani and Papedemos (1980, 1983) and Papedemos and Rozwadowski (1983). Stiglitz and Weiss (1987), Greenwald and Stiglitz (1987), Blinder (1985) and Bernanke and Gertler (1987), among others, posit theories of equilibrium credit rationing which imply important linkages between credit and income. These models suggest that credit movements are indeed a driving force within the macroeconomy, and that credit does not merely react passively to movements in liabilities of financial institutions, especially in the short run. Unfortunately, any lead/lag relationship between assets and liabilities may be masked by the periodicity of the available data, making these distinctions difficult to isolate empirically. Still, some of these stories are logically powerful and bear consideration and investigation.

The simplest and perhaps most compelling arguments for investigating credit are found at a practical level. While total assets must equal total liabilities on any balance sheet, subsets of assets and liabilities

are rarely equal. Monetary and credit aggregates not only contain selected financial assets or liabilities, but also are constructed according to different rules. Whether or not to include a liability in a monetary aggregate is generally decided on the basis of the liability's liquidity, which leads to a spectrum of narrow to broad monetary aggregates. Credit instruments, however, tend to be aggregated on the basis of the type of debtor. Thus credit aggregates cannot, in general, be matched one-for-one with monetary aggregates. Their movements will not be perfectly correlated, and there is scope for both credit and monetary aggregates to act as indicators of future movements in macroeconomic variables. At the very least, comparison of data from both sides of the balance sheet will provide useful corroboration and information, particularly when exploring abnormal behaviour in either the money or credit markets.

In light of the preceding, it seems useful to define a comprehensive set of credit aggregates and to perform a systematic appraisal of their information content. The aim is to isolate those measures of credit which display potential as contemporaneous and leading indicators of nominal spending (YGNE), real spending (UGNE) and prices (PGNE) - the three goal variables[1] - and then to specify equations which link the goal variables with the financial indicators.

The techniques used to address these questions have evolved over the past decade as the indicator properties of the many monetary aggregates have been appraised. The methodology used in this study follows that of Hostland, Poloz and Storer (1988), henceforth HPS, in their analysis of the information content of a wide range of monetary aggregates. This permits direct comparison of the results obtained for credit with those found for money. As such, this report and that of HPS

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1. Given the high correlations between these and other measures of income and prices, Hostland, Poloz and Storer (1988) suggest that the set of goal variables can be restricted to real and nominal GNE and the GNE price deflator. They find that the correlations between GNE and the monetary aggregates and GDP and the monetary aggregates are virtually identical, and conclude that it does not appear necessary to carry both of these measures of income through the analysis. It should also be noted that the GNE and GDP deflators are identical in Statistics Canada's methodology.

on the monetary aggregates can be considered companion studies which evaluate the indicator properties of both monetary and credit aggregates in a comprehensive and comparable framework.

As the performance of the monetary and the credit aggregates is compared throughout the paper, a brief synopsis of results obtained by HPS for the monetary aggregates is required here. After analysis of forty-six monetary aggregates, they conclude that the broad M2 and M2+ aggregates are the strongest contemporaneous indicators of nominal spending. In terms of leading indicators, nominal M1 is most informative about nominal spending and real M1 is most informative about real spending, while M2 contains the most information about future price movements.

The comparisons of the monetary and credit measures focus initially on the substitutability of these two types of aggregates acting individually in the indicator arena and later on the more important question of whether credit contains information which is not already provided by the monetary aggregates. Thus the role of credit aggregates as indicators of prices, real and nominal spending is examined from two perspectives: as substitutes for or checks on the monetary aggregates, and as bearers of information which is not captured by the monetary aggregates.

2 THE CREDIT AGGREGATES

A brief description of each of the credit aggregates, the mnemonics and the data sources is given in Table 1. The data are based upon standard public and private credit measures. In some cases, these aggregates are augmented by extra data from near-banks. Other measures exploit some of the attractive features of the available data. The resulting aggregates can be divided into three categories. The first group consists of the standard measures of private credit and the corresponding augmented or "plus" aggregates. The second group contains an aggregate measure of public debt (federal, provincial and municipal)

Table 1:

THE CREDIT AGGREGATES: MNEMONICS

Mnemonic	Description	Start Date
I. (A) Standard Aggregates		
CSTB	short-term business credit	1969Q1
COB	other business credit	1969Q1
CTB	total business credit	1969Q1
CC	consumer credit	1969Q1
CRM	residential mortgage credit	1969Q1
CTH	total household credit	1969Q1
PRIVATE	total household + business credit (private credit)	1969Q1
I. (B) Plus Aggregates		
CTBP	total business credit + TML data	1973Q3
CCP	consumer credit + credit union data	1969Q1
CRMP	residential mortgage credit + credit union data	1969Q1
CTHP	total household credit + credit union data	1969Q1
PRIVPA	total household and business credit + credit union household data	1969Q1
PRIVPB	total household and business credit + TML business and credit union household data	1973Q3
II. Public Debt		
PUBLIC	federal, provincial and municipal debt	1970Q2
TOTAL	total public + private debt	1970Q1
TOTPA	total public + private debt + credit union household data	1970Q1
TOTPB	total public + private debt + TML business and credit union household data	1973Q3
III. Credit Extended by Chartered Banks		
CSTBBK	short-term business credit	1969Q4
COBBK	other business credit	1969Q1
CTBBK	total business credit	1969Q4
CTHBK	total household credit	1969Q1
CTBK	total household and business credit	1969Q4
PRSLN	personal loans	1969Q1
BSLN	business loans	1969Q1
MJASST	major asset holdings	1969Q1

and economy-wide debt (private plus public debt). The last group comprises measures of credit extended by the chartered banks. The construction of the aggregates in each of the three categories is described in more detail below.

Table E1 - Selected indicators of money and credit - in the Bank of Canada Review reports the seven standard measures of private credit. The data are monthly and are available from the late 1960s. Short-term business credit (CSTB) consists of business loans, leasing receivables and non-residential mortgages at chartered banks, sales finance and consumer loan companies and financial institutions affiliated with foreign banks; outstanding commercial paper of non-financial businesses; bankers' acceptances; foreign currency loans to residents (excluding the federal government) by chartered banks; and foreign currency business financing by financial institutions affiliated with foreign banks.[2] Other business credit (COB) includes outstanding bonds and shares of non-financial businesses. Consumer credit (CC) sums estimated consumer credit outstanding at chartered banks, sales finance and consumer loan companies, trust and mortgage loan companies, life insurance companies, department stores and Quebec savings banks. Residential mortgage credit (CRM) consists of the estimated mortgage loans extended by the same financial institutions (excluding department stores).[3]

Where possible, credit union and trust and mortgage loan company (TML) data have been added to the standard debt measures to obtain "plus" aggregates. Data for TML business loans and leasing receivables are available since the early 1970s. These series are added to total business credit to obtain CTB plus (CTBP). Household credit extended by the credit unions is added to the measures of consumer credit, residential mortgage credit and total household credit to create CCP, CRMP and CTHP.[4] Two

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2. The institutions affiliated with foreign banks all became schedule B chartered banks in the early 1980s.

3. See Bank of Canada Review: Notes to the tables, 1987, pp. 20-21.

4. Credit union data are quarterly, end-of-period. In order to be approximately consistent with the other monthly data, the numbers for the current and preceding quarter are averaged (to obtain an "average" value) for the current quarter.

plus measures of total private credit are calculated. One includes only the plus component for household credit; the other includes the plus components for both business and household credit.[5]

The public debt series includes loans extended to and bills issued by federal, provincial and municipal governments, and guaranteed bonds issued by provincial and municipal enterprises.[6] Total credit is obtained by summing private and public credit.

The last group of aggregates is derived from data reported regularly by the chartered banks. The frequency and timeliness of these numbers would make them very attractive policy guides if they were to reveal leading or even contemporaneous information on nominal spending. An attempt was made to construct chartered bank credit measures that coincided, in composition, with the standard measures of private debt. In addition, three other chartered bank series have been examined: personal loans (PRSLN), business loans (BSLN) and total major assets (MAJASST). These data are reported in the Bank of Canada Review.

These three groups of credit aggregates provide a comprehensive data base which is analyzed extensively throughout the remainder of this study.

3 TRENDS IN RATIOS OF NOMINAL SPENDING TO CREDIT

As a preliminary analysis of the credit aggregates, the stability of the ratio of nominal spending to each of the credit aggregates is investigated over the 1971-85 time period. While a stable YGNE to credit ratio is not a necessary characteristic of an indicator for nominal spending, the variability of YGNE/credit gives some crude insight into whether or not nominal spending and the aggregate have tended to move together over the sample period. The results of this analysis can be compared to those presented by B. Friedman for broad credit in the United

5. An aggregate with only the household plus component was created due to the fact that business plus aggregates are valid over a shorter sample period.

6. Bonds issued by provincial and municipal enterprises are not included in the private business credit measures.

States. Since the apparent stability of the ratio of income to broad credit (before 1982) was Friedman's principal argument for advocating credit targeting, it is of interest to determine whether the result holds for Canada.[7]

The natural logarithm of the ratio of nominal GNE to each credit aggregate is regressed on (a) a constant and a time trend and (b) a constant, a time trend and the 90-day rate on prime commercial paper (R90) over three sample periods: (i) 71Q1-85Q4, (ii) 79Q1-85Q4 and (iii) 75Q1-85Q4.[8] The first specification is used to quantify the movement in the ratio of nominal spending to credit, which can be explained by a linear time trend. As simple theory indicates that interest rates should explain variation in both nominal spending and the aggregate, specification (b) represents a logical modification of (a). A subset of the regression results is presented in Tables 2 and 3. Of interest are the sign and slope of the trend, and the standard deviation of the estimated equation. The latter is used to measure the "noisiness" of the trend in YGNE/credit. Following the rule that the least noisy relationship is best, the aggregates are ranked according to the standard deviations of the regressions.

Listed in Table 2 are the top ten credit aggregates over each of the sample periods, excluding and including R90 as an explanatory variable in the equation. As an initial comment, it is reassuring to see a fair degree of consistency in the rankings across the three sample periods. Not surprisingly, the broad aggregates - total private (PRIVATE) and total public and private (TOTAL) debt - and the corresponding plus aggregates exhibit the most stable ratios with nominal spending. This result is intuitive, since the broad aggregates internalize any shifting between

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7. Previous studies using Canadian data (for example, Brittain 1981) have not found ratios of nominal spending to credit to be exceptionally stable relative to the velocities of many of the monetary aggregates (Y/M). However, only a limited set of credit aggregates has been investigated and none was as broad as Friedman's preferred aggregate - total non-financial debt. (Total non-financial debt sums all credit market liabilities of non-financial sectors. This corresponds most closely to the TOTAL measure used here).

8. The first two sample periods are consistent with those used in HPS. The 75Q1-85Q4 sample period is added in order to examine the plus aggregates, which include business credit over the longest possible sample period.

Table 2:

TRENDS IN RATIOS OF NOMINAL GNE TO CREDIT:
RANKED BY STANDARD DEVIATION (LOWEST TO HIGHEST)

I. R90 Not Included in the Regression

Rank	71Q1-85Q4	75Q1-85Q4	79Q1-85Q4
1	PRIVPA	TOTAL	TOTPB
2	PRIVATE	TOTPB	TOTPA
3	TOTAL	TOTPA	CRM
4	TOTPA	COB	TOTAL
5	MJASST	PUBLIC	CTH
6	CCP	PRIVPB	CTHP
7	CC	PRIVPA	COB
8	CTH	PRIVATE	CCP
9	CTBK	CCP	CC
10	CTHP	CC	PRSLN

II. R90 Included in the Regression

Rank	71Q1-85Q4	75Q1-85Q4	79Q1-85Q4
1	PRIVPA	TOTPB	TOTPB
2	PRIVATE	TOTAL	COB
3	CC	PUBLIC	TOTPA
4	TOTPA	TOTPA	CRM
5	CCP	COB	PUBLIC
6	MJASST	PRIVPB	TOTAL
7	TOTAL	PRIVPA	CTH
8	CTH	PRIVATE	CTHP
9	CTBK	CC	PRSLN
10	CTHP	CCP	CC

credit instruments inside and outside the definitions of less comprehensive aggregates.[9] Many of the measures of household and business credit rank in the top ten for both specifications in all three sample periods. The equations for household credit (consumer credit and residential mortgage credit) tend to fit the data better than the business credit equations. Other business credit (COB) does perform well in the two shorter sample periods but does not rank highly for the full 1971-85 time period. Of the chartered bank credit aggregates, the equations for total major assets (MAJASST) and total household and business credit (CTBK) fit well enough over the long sample, 71Q1-85Q4, to rank in the top ten. However, the general lack of stability of the chartered bank aggregates might have been anticipated as a result of (i) shifts between intermediated and unintermediated credit and (ii) substitution between credit extended by chartered banks and other financial intermediaries during the 1970s and 1980s.[10]

In Table 3 the estimated trends and the standard deviations for the YGNE/credit equations provide some indication of the range of results which are obtained for the credit aggregates. While the majority of the nominal spending to credit ratios exhibit negative trends, the consumer credit ratio is positively trended over the 1971-85 sample period. The ratios of YGNE to CSTB (short-term business credit) and YGNE to the chartered bank business credit aggregates have steep negative trends. Thus there is considerable diversity (and sample sensitivity) of the size and sign of the trend movements in the ratios of nominal spending to credit.

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9. Substitution between more or less liquid types of deposits and between deposits at chartered banks and other financial intermediaries have distorted the trend movements in some of the narrow monetary aggregates. As the credit measures aggregate on the basis of the type of debtor (rather than liquidity) and include most sources of financing, there is less scope for substitution between different credit aggregates.

10. For more discussion of recent innovations and trends in business and household credit see Houde (1987) and Tetlow (1986).

Table 3:

RATIOS OF NOMINAL GNE TO CREDIT
(STATISTICS IN PER CENT PER YEAR)

I. R90 Not Included in the Regression

	Sample: 71Q1-85Q4			Sample: 75Q1-85Q4		
	Trend	SE	Rank	Trend	SE	Rank
CSTB	-5.36	9.26	14	-4.85	10.59	21
COB	2.77	10.42	20	0.27	3.11	4
CTB	-0.96	7.90	11	-2.42	5.79	12
CC	0.07	5.93	7	1.10	5.34	10
CRM	-2.53	8.37	12	-0.90	7.02	17
CTH	-1.50	7.20	8	-0.14	6.19	14
PRIVATE	-1.12	4.79	2	-1.62	4.63	8
CCP	-0.22	5.83	6	0.78	5.31	9
CRMP	-3.32	9.59	16	-1.49	8.05	19
CTHP	-2.08	7.87	10	-0.62	6.85	16
CTBP	-	-	-	-2.50	5.57	11
PRIVPA	-1.38	4.43	1	-1.71	4.62	7
PRIVPB	-	-	-	-1.76	4.44	6
PUBLIC	-1.98	9.26	14	-3.88	4.20	5
TOTAL	-1.50	5.36	3	-2.59	1.88	1
TOTPA	-1.62	5.02	4	-2.61	1.97	3
TOTPB	-	-	-	-2.63	1.89	2
CSTBBK	-6.00	9.95	18	-6.28	11.58	24
COBBK	-6.73	20.42	21	-5.78	22.52	25
CTBBK	-6.05	9.57	15	-6.21	11.15	22
CTHBK	-4.61	8.57	13	-2.89	6.14	13
CTBK	-5.55	7.60	9	-5.03	8.57	20
BSLN	-3.49	10.04	19	-2.96	11.45	23
PRSLN	-1.63	9.78	17	0.33	7.63	18
MJASST	-2.27	5.79	5	-1.97	6.58	15
Memo:						
M1	3.99	3.60		4.48	3.06	
M2	-1.09	3.18		-1.23	3.40	

II. R90 Included in the Regression.

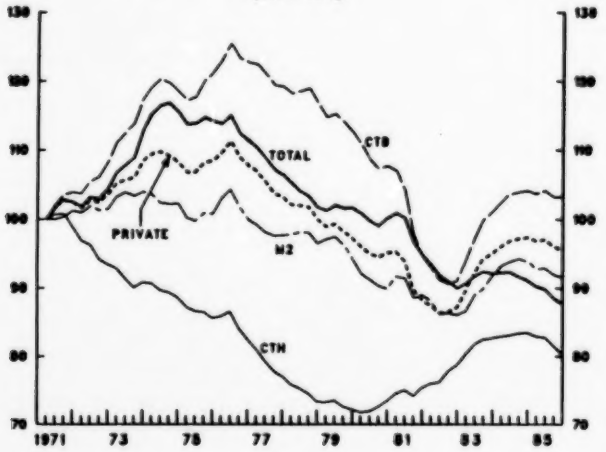
CSTB	-4.39	7.40	12	-4.09	8.31	21
COB	-1.99	9.43	21	0.03	2.48	5
CTB	-0.92	7.97	15	-2.11	5.13	11
CC	0.68	4.79	3	1.49	4.07	9
CRM	-1.86	7.48	13	-0.53	6.27	18
CTH	-0.86	6.24	8	0.24	5.26	13
PRIVATE	-0.89	4.64	2	-1.29	3.59	8
CCP	0.32	4.95	5	1.13	4.39	10
CRMP	-2.56	8.51	19	-1.06	7.21	20
CTHP	-1.42	6.92	10	-0.23	5.99	16
CTBP	-	-	-	-2.20	4.98	12
PRIVPA	-1.09	4.31	1	-1.39	3.50	7
PRIVPB	-	-	-	-1.42	3.36	6
PUBLIC	-2.99	7.22	11	-4.32	1.93	3
TOTAL	-1.78	5.15	7	-2.56	1.90	2
TOTPA	-1.86	4.87	4	-2.57	1.96	4
TOTPB	-	-	-	-2.60	1.89	1
CSTBBK	-5.23	8.96	20	-5.58	9.89	24
COBBK	-5.85	19.95	22	-4.85	21.21	25
CTBBK	-5.27	8.49	18	-5.50	9.25	23
CTHBK	-4.09	8.08	16	-2.68	5.92	15
CTBK	-4.85	6.47	9	-4.49	7.18	19
BSLN	-2.38	7.73	14	-2.11	8.73	22
PRSLN	-0.73	8.32	17	0.86	6.07	17
MJASST	-1.75	5.14	6	-1.58	5.63	14
Memo:						
M1	3.87	3.57		4.34	2.82	
M2	-0.91	3.03		-1.02	2.89	

Notes:

S.E. = standard error of the equation
Rank is from lowest to highest standard error of the equation

For visual comparison of the relative stability of the ratios of nominal spending to the M2 and some of the credit aggregates, Chart 1 depicts the YGNE/M2, YGNE/TOTAL (total credit), YGNE/CTB (total business credit), and YGNE/CTH (total household credit). The graph indicates that the ratios YGNE/TOTAL and YGNE/PRIVATE have not been particularly stable relative to YGNE/M2. Comparison of the regression results reveals that YGNE/M2 and YGNE/M1 have been more "stable" than YGNE/TOTAL over the 71Q1-85Q4 period, but less "stable" over the 75Q1-85Q4 sample period (where stability is measured by the standard error of the regression).

CHART 1
RATIOS OF YGNE TO SELECTED CREDIT AND MONETARY AGGREGATES
(1971=100)



4 CORRELATION ANALYSIS

Correlations between nominal GNE, real GNE and the price deflator, and contemporaneous and lagged values of the twenty-five credit aggregates draw a more detailed picture of the relationships between the aggregates and the goal variables. The data are in four-quarter growth rates to moderate short-run noise and to focus attention on longer-run movements. A strong correlation between contemporaneous values of an aggregate and nominal GNE would suggest that the aggregate has the potential to act as

an indicator of contemporaneous nominal spending, assuming that data on the aggregate are available on a more timely basis than data on nominal spending.

The correlations are calculated over three sample periods: 71Q1-85Q4, 79Q1-85Q4 and 71Q1-85Q4 with ten quarters, 82Q3-84Q4, excluded from the sample period. The unusual movements in the monetary aggregates over the 1982-84 period have been discussed in detail in Bank of Canada Review articles.[11] The interpretation offered is that with the high level of interest rates firms and households tended to sell liquid assets in order to pay off some of their outstanding debt, resulting in a marked consolidation of private sector balance sheets. Following the methodology in HPS, calculation of correlations over the "gapped" sample provides some insight into the influence of this unusual episode on the relationships between growth of credit and the goal variables. The contemporaneous correlation results are synthesized in Table 4 and the remainder of this section discusses these as well as the correlations with lagged values of credit.

The household credit aggregates - total household credit (CTH), consumer credit (CC) and residential mortgage credit (CRM) - yield the highest correlations with nominal GNE. The strongest correlations are contemporaneous rather than lagged.

The highest correlations between real spending and credit are realized at a variety of lags for the different aggregates. In general, though, the correlations peak at two and three lags of the four-quarter growth rates. In the 71Q1-85Q4 sample period, the highest correlations are: total business credit - CTB(3,-79),[12] chartered bank short-term business credit - CSTBBK (3,-72), and total household and business credit - PRIVATE(4,64). Over the shorter 79Q1-85Q4 sample, the second lag of the

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11. See for example, "Monetary aggregates: some recent developments," Bank of Canada Review, February 1987, pp. 3-16.

12. The first number in the parentheses refers to the lag on the aggregate; the second number, to the correlation coefficient, expressed in percentage terms.

Table 4:

CONTEMPORANEOUS CORRELATIONS BETWEEN THE CREDIT AGGREGATES, NOMINAL GNE, REAL GNE AND PRICE
(expressed as per cent)

	Rank	71Q1-85Q4	79Q1-85Q4	71Q1-85Q4/ 82Q3-84Q4 excluded
YGNE:	1	CTH (77)	CTHP (81)	CC (78)
	2	CCP (76)	CTH (80)	CCP (75)
	3	CTHP (76)	PRSLN (79)	CTH (73)
	4	CC (76)	CRMP (78)	CTHP (69)
	5	CRM (73)	CRM (75)	CRM (65)
UGNE:	1	PRSLN (-58)	CTBK (-52)	PRSLN (79)
	2	CCP (55)	CSTBBK (-51)	CCP (64)
	3	CTHP (55)	CTBBK (-51)	CTB (-64)
	4	CRMP (54)	CTHP (51)	CTBP (-64)
	5	CTH (51)	CRMP (50)	CC (60)
PGNE:	1	CSTB (82)	CTB (86)	CSTB (85)
	2	PRIVATE (74)	CTBP (86)	PRIVATE (79)
	3	CSTBBK (74)	CSTB (86)	PRIVPA (78)
	4	PRIVPA (72)	PRIVATE (83)	PRIVPB (78)
	5	PRIVPB (72)	CSTBBK (83)	CSTBBK (70)

4-quarter growth rates of chartered bank short-term business credit - CSTBBK (2,-90) and total business credit - CTBBK(2,-88) are relatively strongly correlated with UGNE.

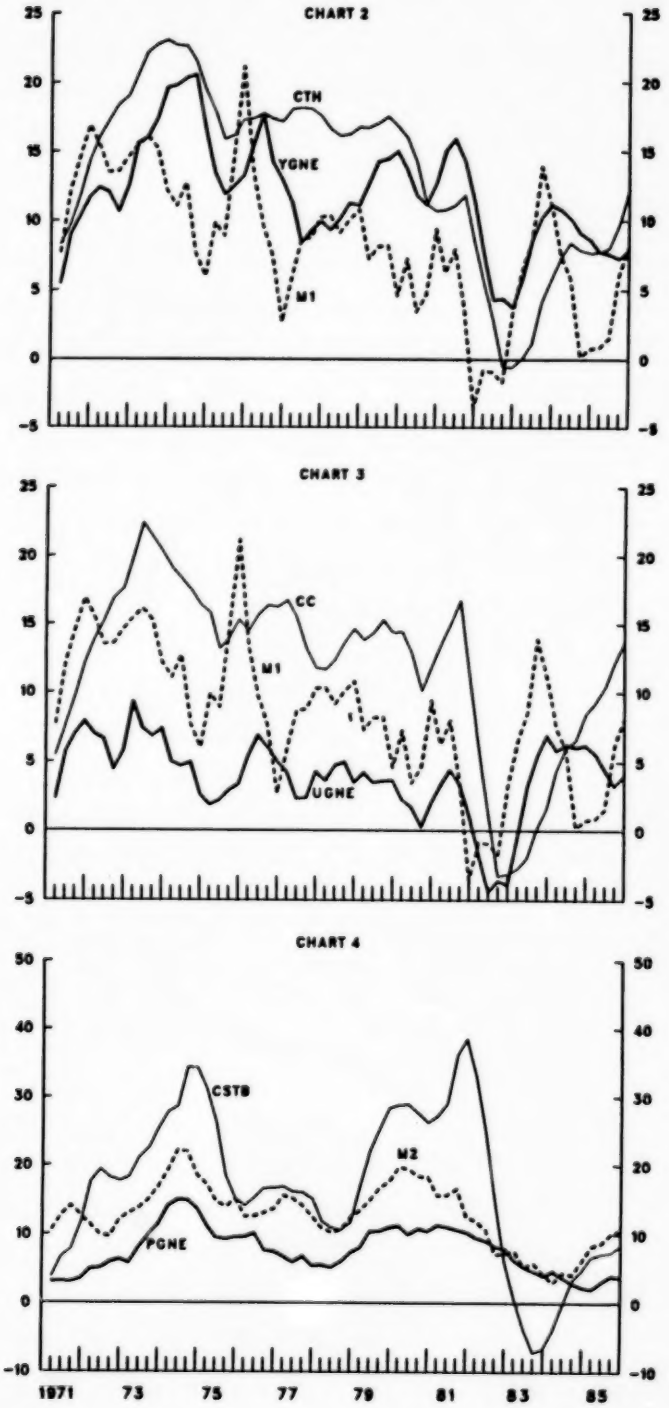
For prices, as for nominal spending, the highest correlations are found with contemporaneous credit aggregates. Contemporaneous short-term business credit - CSTB(0,82), and total household and business credit - PRIVATE(0,74) perform well.

A quick comparison of the correlation results for monetary and credit aggregates may be gleaned from Charts 2 to 4 of the four-quarter growth rates in YGNE, UGNE, PGNE and the monetary and credit aggregates which yield the strongest correlations with each of the goal variables. The highest correlations between credit and nominal GNE or the GNE deflator are contemporaneous, whereas for the monetary aggregates the highest correlations are at one and two lags of the four-quarter growth rates. As the "best" contemporaneous correlations for money and credit are of the same order of magnitude, it follows that the lagged correlations between money and the goal variables YGNE and PGNE exceed lagged and contemporaneous correlations for credit and the goal variables. For real income, there is no obvious ranking of the monetary and credit aggregates in the context of the correlation analysis. In any case, definitive statements on the leading information content of credit relative to money require the more sophisticated investigative techniques applied in the next section.

5 THE INFORMATION CONTENT OF CREDIT AGGREGATES

The information content of the credit aggregates is probed more deeply by constructing bivariate and multivariate vector autoregression models for nominal income, real income and prices with the credit aggregates and by examining the performance of the estimated models. As the methodology is atheoretical, the resulting models cannot be used to make structural inferences about the economy. They can, however, be judged according to their ability to track and forecast movements in the goal variables. It is also possible to compare the performance of these

FOUR-QUARTER GROWTH RATES OF SELECTED
MONETARY AND CREDIT AGGREGATES



models with that of the models derived from the monetary aggregates and thus determine whether there is a role for measures of credit in the set of macroeconomic indicators.

The methodology used to construct the indicator models is described in detail in HPS and summarized briefly here. The bivariate models regress one-quarter growth rates of each goal variable on a constant, lagged values of the dependent variable, and contemporaneous and lagged one-quarter growth rates of a credit aggregate over the 71Q1-85Q4 sample period.[13] Previous work has found that one-quarter growth rates of YGNE, UGNE and PGNE are stationary time series (see HPS). A maximum of ten lags of the lagged dependent variable and of the credit aggregate is permitted; the optimal lag structure is chosen in order to minimize Akaike's Final Prediction Error (FPE).[14] The models which obtain the lowest FPE are subjected to comparisons, tests and modifications.

Multivariate models are constructed by allowing lagged values of financial variables - an interest rate, a bilateral Canada/U.S. exchange rate and a stock market price index - to enter the bivariate equations.

The encompassing methodology of Hendry and Richard (1982) permits comparison of the information provided by non-nested models. Rolling Chow tests are used to investigate the stability of the models. Finally, the

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13. Initially, the models were estimated over the 72Q1-85Q4 sample to allow for a maximum of ten lags on the credit aggregates. As most of the optimal lag lengths chosen were quite short, the equations were reestimated starting in the first quarter of 1971. None of the models which required long lags on the credit aggregates performed strongly enough to merit particular attention. Thus we focus on the long-sample results. The models were also estimated over sample periods ending in 1982Q2, in order to purge the effects of the last recession and of the 1982-84 period from the results. As there was no significant change in the rankings of the aggregates according to the minimum FPE criterion, these sample periods are not considered further here.

14. Given the estimated equation:

$$(1)\quad Y = A^{p}(L)\,Y + B^{q}(L)\,C + u$$

Akaike's FPE is calculated as:

$$(2)\quad FPE(q) = (T + p + q + 1)/(T*(T - p - q - 1))*SSR$$

where T is the number of observations, p is the number of lags on Y, q is the number of lags on credit (C) and SSR is the sum of the squared residuals from (1). Note that if contemporaneous credit is also included in the equation, then q is equal to the number of lags on credit plus 1.

models are used to generate one-quarter-ahead forecasts for the 75Q1-86Q4 period; the root-mean-squared forecast errors provide another criterion for ranking the indicator models.

Throughout this section, the performance of the credit models is compared with that of the preferred bivariate and multivariate models which HPS constructed from the monetary aggregates. Comparison is made by examining the in-sample fit and the forecast errors for the different models. As such, credit and money are matched against one another. In the last part of this section, encompassing tests are used to determine whether credit adds significant information to models which already use the information given by the monetary aggregates.

5.1 Bivariate Models

Bivariate models were built by introducing contemporaneous and lagged values of a single credit aggregate into the established autoregressive models.

While HPS construct bivariate models from the monetary aggregates which include only lagged values of the aggregate, the bivariate credit equations have been estimated both including and excluding contemporaneous credit because the correlation results described in the previous section suggest that contemporaneous credit contains most of the information for both nominal income and prices. The models which include only lagged values will be referred to as BIMs (bivariate indicator models) to correspond with the terminology used for the monetary indicator models. The models which include contemporaneous credit will be called CIMs (contemporaneous indicator models). The value of "contemporaneous" models is less obvious than that of models which incorporate only lagged values of the explanatory variables, since their usefulness in forecasting derives only from the presumption that the collection of data is more rapid for the explanatory variables (in this case, credit) than for spending. Simultaneity between the dependent variable and the contemporaneous credit aggregate could bias the model estimates. However, the seriousness of the simultaneity problem is largely mitigated by the

lack of structural content of the models. Since the purpose of this paper is to evaluate the information content of credit aggregates, contemporaneous and lagged, the results for the CIMs are worth considering.

As a benchmark for evaluating the performance of the bivariate models, the estimated autoregressive models for nominal GNE, real GNE and the GNE price deflator are presented in Table 5. The FPE criterion chose simple lag structures of one, one and two lags on nominal income, real income and prices respectively.[15]

Using the FPE ranking, the results for the bivariate models have been distilled into Table 6, which reports summary statistics for the models which give the lowest FPE including and excluding contemporaneous credit.[16]

For nominal spending, household credit aggregates consistently exhibit the lowest FPE. In models which include contemporaneous credit, residential mortgage credit (CRM), total household credit (CTH) and consumer credit (CC) perform best. These household credit measures enter the equations with no lags, according to the FPE criterion for choosing lag length. The models constructed with total business credit (CTB) and total private credit (PRIVATE) perform somewhat more poorly than the household credit models, with FPEs of 0.998 and 0.997 respectively, against FPEs below 0.84 for CRM and CTH. In models which exclude contemporaneous values, CRM and CTH lagged one quarter, and total bank credit to households (CTHBK) with 5 lags, rank highly. As for the CIMs, the best broad credit measure, PRIVATE, and total business credit, CTB, have higher FPEs than the household credit models. The summary statistics - $\bar{R}^2$ and FPE - indicate that the contemporaneous models fit the data marginally better than the models which include lagged credit only.

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15. For further discussion of the appropriateness of the specifications of these univariate models and the properties of the error terms, the reader is referred to HPS.

16. As FPE results for the plus aggregates were very similar to those given by the standard credit aggregates, we focus solely on the latter in the remainder of the analysis.

Table 5:

UNIVARIATE MODELS FOR YGNE, UGNE AND PGNE
(All data are in one-quarter growth rates)

Sample period: 71Q1-85Q4[1]

YGNE = 1.251 + 0.563*YGNE(-1)[1]
(3.862) (5.316)
$\bar{R}^2$ = 0.316 SSR = 54.528 SER = 0.97

UGNE = 0.647 + 0.345*UGNE(-1)
(3.725) (0.946)
$\bar{R}^2$ = 0.104 SSR = 57.975 SER = 1.00

PGNE = 0.351 + 0.407*PGNE(-1) + 0.402*PGNE(-2)
(1.759) (3.290) (3.293)
$\bar{R}^2$ = 0.527 SSR = 22.897 SER = 0.634

1 These results differ from those reported in HPS due to the July 1987 revisions in National Accounts data.

SSR = sum of squared residuals
SER = standard error of the regression

Table 6:

CREDIT AGGREGATES AS INFORMATION VARIABLES FOR YGNE, UGNE AND PGNE

Sample Period: 71Q1 - 85Q4

Credit Aggregate	Lag on Credit	$\bar{R}^2$	SER	FPE
	(i) 71Q1-85Q4			
(a) YGNE				
(i) contemporaneous credit included				
CRM	0	0.427	0.887	0.826
CTH	0	0.420	0.893	0.837
CC	0	0.367	0.933	0.913
Memo:				
CTB	0	0.308	0.975	0.998
PRIVATE	0	0.309	0.975	0.997
TOTAL	0	0.306	0.977	1.002
(ii) contemporaneous credit excluded				
CRM	1	0.381	0.922	0.893
CTH	1	0.370	0.930	0.909
PRSLN	5	0.376	0.926	0.957
Memo:				
CTB	1	0.312	0.973	0.993
PRIVATE	1	0.304	0.978	1.004
TOTAL	1	0.307	0.976	1.000
M1	2	0.495	0.833	0.740
(b) UGNE				
(i) contemporaneous credit included				
CTH	3	0.308	0.879	0.850
CRM	2	0.264	0.906	0.890
CC	3	0.240	0.921	0.934
Memo:				
PRIVATE	2	0.224	0.930	0.938
TOTAL	3	0.172	0.961	1.016
(ii) contemporaneous credit excluded				
CTBBK	2	0.273	0.900	0.865
CRM	2	0.213	0.937	0.937
PRIVATE	2	0.210	0.939	0.940
Memo:				
TOTAL	3	0.186	0.953	0.985
M1/PGNE	5	0.371	0.838	0.784
(c) PGNE				
(i) contemporaneous credit included				
CSTB	0	0.576	0.600	0.384
BSLN	0	0.573	0.602	0.387
CC	0	0.568	0.606	0.392
Memo:				
CTH	0	0.566	0.607	0.393
PRIVATE	0	0.564	0.609	0.395
TOTAL	0	0.522	0.637	0.433
(ii) contemporaneous credit excluded				
CC	1	0.558	0.612	0.400
CTH	1	0.558	0.613	0.401
PRIVATE	1	0.555	0.615	0.403
CRM	1	0.549	0.619	0.408
Memo:				
TOTAL	1	0.521	0.638	0.434
M2	2	0.597	0.585	0.371

As anticipated by the correlation results, the credit aggregates enter the bivariate models for real spending with longer lags than in the nominal spending equations. Again, the three measures of household credit dominate the top rankings for the CIMs. Residential mortgage credit, total household credit and consumer credit enter the models with contemporaneous and two, three and three lags respectively. For the BIMs, total business credit extended by chartered banks (CTBBK) with two lags produces the lowest FPE of 0.865, followed by residential mortgage credit (CRM) and PRIVATE, both with two lags, with FPEs of 0.937 and 0.940 respectively.

The preference for short or no lags on the credit aggregates re-emerges in the price equations. Short-term business credit (CSTB), business loans extended by chartered banks (BSLN), consumer credit (CC) and total household credit (CTH) yield the most informative CIMs. In each case, the FPE is minimized when only contemporaneous credit is included in the equation. Of the models which exclude contemporaneous credit, CC, CTH, PRIVATE and CRM give the lowest FPEs. It should be noted, however, that the differences in FPE generated by the price models are small, so the ranking of the models on the basis of this statistic may not be very robust.

A quick comparison of the $\bar{R}^2$ and FPE for the monetary and credit models indicates that the performance of the monetary models is somewhat better than that of the credit models. The nominal spending BIM constructed from two lags of M1 has a $\bar{R}^2$ of 0.495 and a FPE of 0.740,[17] whereas the "best" credit model, CRM (0),[18] obtains a $\bar{R}^2$ of 0.427 and FPE of 0.826. For real spending the BIM constructed with five lags of M1/PGNE yields a $\bar{R}^2$ of 0.371 and a FPE of 0.784. The highest ranked credit model

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17. The results for the monetary aggregates differ from those reported in HPS due to revisions to National Accounts income and price data. The equations have been reestimated with the revised data so that direct comparison with the credit results is possible.

18. The bracketed number refers to the number of lags of the aggregate which are included in the model. (A "0" means that only contemporaneous credit is used.)

for UGNE, the CTH CIM, obtains a $\overline{R}^2$ of 0.308 and a FPE of 0.850. For prices, the M2(-2) BIM has a $\overline{R}^2$ of 0.597 and a FPE of 0.371, while the $\overline{R}^2$ and FPE for the CSTB CIM are 0.576 and 0.384 respectively. More definitive comparison of the relative performances of the money and credit models requires the encompassing methodology which is applied in following sections.

5.2 Encompassing Tests

In this section, the "encompassing principle" of Hendry and Richard (1982) is applied in order to compare the information provided by alternative credit models. Given models (1) and (2) below,

$$(1)\quad Y = A^{p}(L)Y + B^{q}(L)C_1 + u_1$$

$$(2)\quad Y = D^{p}(L)Y + E^{r}(L)C_2 + u_2$$

model (1) is said to encompass model (2) if: (i) the variance of the residuals u_1 is less than the variance of the residuals u_2 , and (ii) the expected value of u_1 given the information provided by model (2) is zero. The first condition establishes that model (1) "variance dominates" model (2). The second condition states that model (2) does not explain the residuals from model (1). Thus model (2) does not contribute significant additional information to model (1).

In this study, the model with the lowest FPE is taken as the variance-dominant model, and an F test is used to check for the joint significance of contemporaneous and lagged values of other "informative" credit aggregates in the model. If the additional aggregate is not significant in the variance-dominant model, then the latter model is said to encompass the former.

In light of our interest in the leading versus contemporaneous indicator properties of the credit aggregates, the encompassing methodology was also applied to determine if the variance-dominant contemporaneous model encompassed the top-ranked BIMs for each goal variable.

The F statistics for the encompassing tests are reported in Table 7. For nominal spending, the equations based upon residential mortgage credit, CRM(0) and CRM(1), are the variance-dominant CIM and BIM respectively. In all cases, the other credit aggregates are encompassed (at the 5% level of significance) by the variance-dominant nominal spending models. The CRM CIM easily encompasses the CRM BIM.

Total household credit, CTH(3), and total bank credit to businesses, CTBBK(2), are the variance-dominant CIM and BIM models for real GNE. The CTH CIM gains significant information (at the 5% level) from two lags of CTBBK. Also, two lags of residential mortgage credit are jointly significant in the CTBBK BIM.

For the price equations, short-term business credit, CSTB(0), is the variance-dominant CIM, while consumer credit, CC(1), is the variance-dominant BIM. Both models encompass (at the 5% level of significance) other highly-ranked credit aggregates. As expected, the CSTB CIM easily encompasses the CC BIM.

To summarize, a rather eclectic set of narrow aggregates has emerged as being most informative about each of the goal variables. The "preferred" bivariate models are reported in Table 8. Business credit is more informative in the real spending and price models than in the nominal spending equations.[19] Household credit measures rank very highly for all three goal variables. Residential mortgage credit (CRM) captures most of the credit information about nominal spending; CTH, CRM and total business credit extended by chartered banks (CTBBK) are most informative about real spending; short-term business credit (CSTB) is most informative about prices. It is these models which provide the basis for the construction of multivariate indicator models in the next section.

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19. It is worth noting that business credit is negatively correlated with real output but positively correlated with prices. This result is consistent with the fact that prices and output are themselves negatively correlated at the margin and might help to explain the relatively poor information content of business credit with respect to nominal spending.

Table 7:

ENCOMPASSING F TESTS FOR BIVARIATE MODELS

Sample Period: 71Q1 - 85Q4

Variance-Dominant Model	Additional Credit Aggregate	F Statistic for significance of additional credit aggregate in variance-dominant model)
(a) YGNE		
(i) including contemporaneous credit; CRM(0) as variance-dominant model		
CRM	CTH	0.042
	CC	0.091
	CRM (1)	0.597
(ii) excluding contemporaneous credit; CRM(1) as variance-dominant model		
CRM	CTH	0.020
	CTHBK	1.440
	PRSLN	1.320
(b) UGNE		
(i) including contemporaneous credit; CTH(3) as variance-dominant model		
CTH	CRM	1.121
	CC	1.637
	CTBBK	5.776**
(ii) excluding contemporaneous credit; CTBBK(2) as variance-dominant model		
CTBBK	CRM	6.042**
	PRIVATE	0.825
(c) PGNE		
(i) including contemporaneous credit; CSTB(0) as variance-dominant model		
CSTB	CTH	2.128
	CC	1.393
	BSLN	0.576
	CC (1)	0.299
(ii) excluding contemporaneous credit; CC(1) as variance-dominant model		
CC	CTH	0.237
	PRIVATE	0.918
	CRM	0.216

* Significant at the 5% level.
** Significant at the 1% level.

Table 8:

BIVARIATE CREDIT MODELS (ESTIMATED OVER 1971Q1-1985Q4)

YGNE = 0.830 + 0.342*YGNE(-1) + 0.299*CRM(0)
(2.600) (2.957) (3.505)

$\bar{R}^2$ = 0.427 SER = 0.887 SSR = 44.857

YGNE = 0.972 + 0.356*YGNE(-1) + 0.249*CRM(-1)
(2.990) (2.797) (2.668)

$\bar{R}^2$ = 0.381 SER = 0.922 SSR = 48.473

UGNE = 0.486 - 0.006*UGNE(-1) + 0.641*CTH(0) - 0.018*CTH(-1)
(1.709) (0.047) (3.169) (0.066)

- 0.025*CTH(-2) - 0.455*CTH(-3)
(0.090) (2.235)

$\bar{R}^2$ = 0.308 SER = 0.879 SSR = 41.720

UGNE = 1.558 + 0.151*UGNE(-1) - 0.027*CTBBK(-1) - 0.154*CTBBK(-2)
(5.574) (1.204) (0.392) (2.098)

$\bar{R}^2$ = 0.273 SER = 0.900 SSR = 45.407

PGNE = 0.379 + 0.265*PGNE(-1) + 0.307*PGNE(-2) + 0.105*CSTB(0)
(2.004) (2.073) (2.551) (2.759)

$\bar{R}^2$ = 0.576 SER = 0.600 SSR = 20.158

PGNE = 0.144 + 0.330*PGNE(-1) + 0.409*PGNE(-2) + 0.118*CC(-1)
(0.673) (2.652) (3.469) (2.245)

$\bar{R}^2$ = 0.558 SER = 0.612 SSR = 21.007

5.3 Models Including Other Financial Variables

Using the structure of the bivariate equations, multivariate indicator models (MIMs) are constructed which incorporate the information provided by other key financial variables. Three such variables are investigated: (i) the 90-day rate on prime corporate paper (R90), (ii) the bilateral Canada-U.S. exchange rate (EX), and (iii) the TSE price index (PTSE).[20] Each of these is introduced sequentially into the bivariate models, allowing for a maximum of four lags on the three additional financial variables.[21] Again, the optimal lag structure is chosen according to the FPE criterion.[22] Also, prices are allowed to lead real spending and vice versa in the UGNE and PGNE models. Multivariate models are constructed only for the bivariate equations which exclude contemporaneous credit, as it did not seem logical to build models which contain current credit but only past values for the interest rate, the exchange rate and the TSE price index. Thus the models are specified as linear functions of lags of the goal variable, lagged credit, lagged values of the other financial variables, and lagged real spending or prices in the price and real spending models respectively. Once again, these models can be compared with multivariate models constructed from the monetary aggregates.

Some of the estimated multivariate models are reported in Table 9. Nominal income equations are built from the bivariate total household credit CTH(1) and residential mortgage credit CRM(1) models. Neither the interest rate nor the exchange rate is significant in any of the nominal income equations, but the TSE price index lagged once is significant in the CTH model. For real GNE, the TSE price index, lagged one quarter, is significant in the chartered bank total business credit CTBBK(2) and residential mortgage credit CRM(2) equations. The FPE criterion leads to

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20. This corresponds to the set of variables that is investigated in HPS.

21. When introducing these variables into the models, all possible orderings for the variables were tried, but there was no effect on the final multivariate specifications.

22. Once the lag structure on the financial variables had been established, the optimal lag on the credit aggregate was recalculated, but in no case did the optimal lag on credit change.

Table 9:

MULTIVARIATE INDICATOR MODELS (ESTIMATED OVER 1971Q1-1985Q4)

YGNE = 0.890 + 0.330*YGNE(-1) + 0.285*CTH(-1) + 0.047*PTSE(-1)
(2.934) (2.72) (2.985) (3.280)

$\bar{R}^2$ = 0.462 SER = 0.860 SSR = 41.384 FPE = 0.788

YGNE = 1.246 + 0.184*YGNE(-1) + 0.210*CRM(-1) + 0.035*PTSE(-1)
(4.32) (1.60) (2.39) (2.66)

+ 0.147*PMLS(-1)
(3.79)

$\bar{R}^2$ = 0.566 SER = 0.772 SSR = 32.816 FPE = 0.646

UGNE = 1.415 + 0.120*UGNE(-1) + 0.010*CTBBK(-1) - 0.165*CTBBK(-2)
(5.057) (0.981) (0.146) (2.318)

+ 0.033*PTSE(-1)
(2.125)

$\bar{R}^2$ = 0.316 SER = 0.873 SSR = 41.963 FPE = 0.827

UGNE = 0.354 + 0.158*UGNE(-1) + 0.605*CRM(-1) - 0.496*CRM(-2)
(1.240) (1.279) (2.300) (2.472)

+ 0.038*PTSE(-1)
(2.480)

$\bar{R}^2$ = 0.279 SER = 0.897 SSR = 44.228 FPE = 0.871

the choice of two lags on the exchange rate in the consumer credit and total household credit credit - CC(1), CTH(1) - equations for prices. However, in each of these equations, an F test did not reject, at the 5% level of significance, the null hypothesis that the coefficients on the first and second lag of the exchange rate are both equal to zero. Hence we find that the TSE price index adds significant information to some of the real and nominal income equations, whereas none of the three additional financial variables is significant in the price equations.

Encompassing tests are used to determine whether or not the variance-dominant multivariate specifications gain measurable information from other highly ranked aggregates (Table 10). For nominal GNE, the MIM constructed from total household credit (CTH) has a lower FPE than the residential mortgage credit (CRM) BIM. As none of the financial variables other than credit is significant in the CRM model for YGNE, the CRM BIM and CTH MIM are compared. The CTH MIM encompasses not only the CRM BIM, but also the CRM CIM. This result suggests that the lagged TSE price index captures the information about nominal income which is contained in contemporaneous credit.

Table 10:

ENCOMPASSING TESTS FOR MULTIVARIATE INDICATOR MODELS

Sample period: 71Q1-85Q4

Variance-dominant model	Additional Credit Aggregate	F Statistic
YGNE:		
CTH(1), PTSE(1)	CRM(1)	1.235
	CTH(0)	1.048
	CRM(0)	2.271
UGNE:		
CTBBK(2), PTSE(1)	CRM(1,2)	6.273**

* Significant at the 5% level.
** Significant at the 1% level.

For real GNE, the chartered bank total business credit (CTBBK) MIM is variance-dominant. As for the bivariate models, two lags of residential mortgage credit are able to explain a significant portion of the CTBBK equation errors.

The multivariate models developed using the credit aggregates thus remain quite simple; at most, one of the three additional financial variables was significant in the original bivariate equation.[23] For nominal and real spending, the multivariate models (which exclude contemporaneous credit) encompass, at the 5% level of significance, the preferred CIMs. For prices, though, very simple bivariate equations based on contemporaneous short-term business credit and business loans at chartered banks explain PGNE with more accuracy than the multivariate models.

When compared, in terms of fit, with the multivariate and bivariate models constructed from the monetary aggregates, the credit models do not do well. For all three goal variables, even the bivariate monetary models obtain higher $\bar{R}^2$ and lower FPE than the MIMs which are developed using the credit aggregates. For nominal spending and prices, the performance of the credit MIMs is much reduced by the exclusion of contemporaneous credit from these models. Only in the real spending models does lagged credit consistently add information to the indicator equations.

5.4 Evaluation of the Credit Models

The bivariate and multivariate credit indicator models are subjected to two types of tests to evaluate their in-sample and extra-sample forecasting ability. First, rolling Chow tests are conducted over the

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23. Given the strong performance of the indicator models constructed with household credit aggregates, the significance of the price of housing as given by the multiple listing service (mnemonic PMLS) was tested in the CTH and CRM MIMs for nominal and real spending, and the CC(1) BIM for prices. Four lags on PMLS were permitted to enter the models and the number of lags was chosen in order to minimize the FPE. One lag of PMLS was optimal and significant in the nominal income and price models, but PMLS was not significant in the real spending equation. Chow tests suggest that the model for prices with CC and PMLS is very unstable. Thus only the YGNE model including PMLS merits interest. The root-mean-squared forecast errors reported in section 5.4 reveal that this model is dominated by the simpler BIMs.

75Q1-82Q4 period. The possibility of a structural break in 1986 is checked also. To examine the forecasting ability of the equations, root-mean-squared forecast errors are calculated for each of the models for the period 75Q1-86Q4, using the following methodology. One-quarter-ahead forecasts are computed by estimating each model over a sample period ending one quarter prior to the forecast and predicting growth in the subsequent quarter. The procedure allows us to examine the ability of the models to track movements in the goal variables in a pseudo-operational framework.[24]

Chow tests are used to examine the null hypothesis of stability of the estimated models. Rejection of this hypothesis at the 10% level of significance is considered evidence of instability.

The bivariate models for nominal GNE which are based upon contemporaneous and once-lagged residential mortgage credit (CRM(0) and CRM(1)) display some evidence of instability in 1979. The total household credit BIM and MIM for YGNE exhibit instability in 1986.

The bivariate and multivariate models for real GNE using total business credit at chartered banks (CTBBK) are plagued by evidence of instability in more than half of the 75Q1-82Q2 period. This result precludes use of these two models as forecasting equations. For all of the other real income models, the data cannot reject the null hypothesis of stability.

Some instability is also found in the price equations. The null hypothesis is rejected in 21 of the 32 quarters tested for the total household credit (CTH) CIM. The data also reject the null hypothesis in six quarters of 1975 and 1976 for the residential mortgage credit price BIM, and in two quarters of the same years for the CTH BIM.

Analysis of forecasting performance provides more insight into the usefulness of the bivariate and multivariate models. Table 11 reports the root-mean-squared errors (RMSE) for the one-quarter-ahead forecasts which

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24. As the lag lengths are specified using a sample period which covers most of the forecast period, the forecast errors should be somewhat less than if the models were used to forecast over future periods. On the other hand, as the models are reestimated mechanically every period, they may overreact to new information, thereby increasing the RMSE. In practice, the use of judgement in the application of these models would operate to reduce this overreaction and the resulting forecast error.

are obtained from the preferred credit and monetary models for the 75Q1-86Q4 sample period. (The models are estimated from 71Q1.) In addition, RMSEs are calculated for the nominal GNE forecasts which are computed by combining the forecasts from the price and real income models. These results are reported in Table 12.

For nominal spending and prices, the minimum RMSE for the credit models exceeds the minimum RMSE for the models based upon the monetary aggregates, but for real income several of the credit models (using contemporaneous credit) forecast as well as the best monetary models. The multivariate M1 equation for nominal spending yields a RMSE of 0.843, while the best credit model (total household credit, CTH, no lags) has a RMSE of 0.923. The residential mortgage credit (CRM) CIM achieves the second-lowest RMSE among the credit models, followed by the multivariate CTH equations for nominal spending. Unfortunately, these three models all exhibited some instability. Forecasts for nominal spending were also constructed by combining real income and price forecasts from the corresponding indicator models. The consumer credit (CC) CIM for UGNE paired with the CC(1) model for prices is able to forecast YGNE over the 75Q1-86Q4 sample with greater precision that the single equations (Table 12). However, the indicator models based upon M1 are still able to best this performance by credit.

For real GNE, the bivariate M1/P model yields a RMSE of 0.980, which is higher than the RMSE of 0.890 obtained by the total household credit CIM. In fact, many of the credit models have RMSE which are less than that of the real M1 bivariate model.

Among the price models, those based on contemporaneous business loans by chartered banks (BSLN), short-term business credit (CSTB) and consumer credit (CC) have the lowest RMSEs. The RMSEs calculated for the credit models are only slightly higher than for the models constructed with the monetary aggregates.

Table 11:

ROOT-MEAN-SQUARED-FORECAST ERRORS (1975Q1-1986Q4)
MODELS ESTIMATED FROM 1971Q1

	Model	RMSE	Rank
YGNE:	CRM(0)	0.945	2
	CTH(0)	0.923	1
	CRM(1)	1.038	6
	CTH(1)	1.015	5
	CTH(1), PTSE(1)	0.971	4
	CTH(1), PTSE(1), PMLS(1)	0.947	3
	M1(2)	0.914	
	M1(8)	1.274	
	M1(2), R90(4), PTSE(1)	0.843	
UGNE:	CTH(0-3)	0.890	1
	CC(0-3)	0.908	2
	CTBBK(1,2)	0.967	3
	CRM(1,2)	0.994	6
	CTBBK(1,2), PTSE(1)	0.991	5
	CRM(1,2), PTSE(1)	0.971	4
	M1/PGNE(5)	0.980	
	M1/PGNE(5), PTSE(1)	1.081	
PGNE:	BSLN(0)	0.597	1
	CSTB(0)	0.620	2
	CC(0)	0.629	3
	CC(1)	0.639	4
	CC(1), PMLS(1)	0.696	5
	M2(2)	0.592	
	FI-PHMS(4)	0.618	
	M2(2), R90(1), PTSE(1)	0.591	
	FI-PHMS(4), UGNE(1)	0.653	

Table 12:

COMBINED PRICE AND REAL INCOME ROOT-MEAN-SQUARED FORECAST ERRORS FOR NOMINAL INCOME (1975Q1-1986Q4) MODELS ESTIMATED FROM 1971Q1

Models for:		
UGNE	PGNE	RMSE for YGNE
CC(0-3)	CC(0)	0.944
CC(0-3)	BSLN(0)	0.943
CC(0-3)	CC(1)	0.901

In conclusion, the bivariate credit models that include contemporaneous credit appear to track the three goal variables best over the 75Q1-86Q4 sample. This is true even for real GNE (that is to say, the CIMs perform best), although three lags of total household credit are included in the "best" real income model, whereas only contemporaneous credit enters the nominal income and price models that generate the most accurate forecasts. Household credit aggregates yield the lowest RMSE for income, and business credit aggregates have the lowest RMSE for prices. Finally, it should be noted that while the monetary models dominate the credit models for nominal spending, credit models which include contemporaneous credit perform almost as well as or better than the monetary models for prices and real spending respectively, according to the RMSE criterion.

5.5 Models Including Money and Credit

In the preceding analysis, the bivariate models constructed from the monetary and the credit aggregates were compared in a cursory fashion on the basis of the $\bar{R}^2$, FPE and RMSE obtained by the different models. Encompassing tests to determine whether or not credit adds significant information to indicator models which already incorporate the information provided by the monetary aggregates will shed more light on the role for credit aggregates, in combination with the monetary aggregates, as indicators of real and nominal spending and prices.

The significance of the top-ranked credit aggregates in the indicator models constructed from the monetary aggregates by HPS is examined. The optimal lag structures chosen for the bivariate models are imposed on the combined models. In some cases, the results are biased in favour of credit by permitting contemporaneous credit to enter the information set, when only lagged money is included the models.

The F statistics for the combined significance of each of the credit aggregates in the various models are given in Table 13. The M1 bivariate and multivariate models for nominal GNE easily encompass the contemporaneous and lagged credit aggregates. For real GNE, however, total business credit extended by chartered banks (CTBBK) is significant (at the 5% level) in the multivariate real M1 model. Residential mortgage credit (CRM) is not. Business loans by chartered banks (BSLN) add significant information to the bivariate M2 model, while short-term business credit (CSTB) is informative in the FI-PHMS bivariate model for the GNE price deflator. The credit aggregates are not significant in either of the multivariate PGNE models based on M2 and FI-PHMS. Credit, therefore, appears to contain some information over and above that contained in the monetary aggregates for real spending and prices, but not for nominal spending.[25] It is also interesting to note that while household credit performs best on its own, it is business credit which contains the most incremental information not already given by the monetary aggregates.

A second encompassing test is used to weigh the information given by the forecasts from the models which are derived from the monetary and the credit aggregates. Actual growth in the goal variable is regressed on a monetary and a credit model forecast for the 75Q1-86Q4 sample period. The recursive one-quarter-ahead forecasts are used, hence the model parameter estimates are updated prior to each one-quarter-ahead forecast. A significant coefficient on the credit model forecast would indicate that that model adds information to the monetary model forecast. The magnitudes of the coefficients on each of the forecasts indicates the weights which should be given to each in order to obtain an "optimal" forecast.

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25. As an alternative to the encompassing methodology, the credit and monetary models were also compared using the J-test developed by Davidson and Mackinnon (1981). In all cases the encompassing and J-tests produced equivalent results.

Table 13:

THE SIGNIFICANCE OF CREDIT IN THE MONETARY INDICATOR MODELS

	Models: Monetary	Credit	71Q1-85Q4 F-Statistic	Critical F statistics (5% level of significance)
YGNE:	M1(2)	CTH(0)	3.157	4.00
		CTH(1)	0.752	4.00
		CRM(0)	2.627	4.00
		CRM(1)	0.774	4.00
	M1(8)	CTH(0)	0.734	4.08
		CTH(1)	0.609	4.08
		CRM(0)	0.242	4.08
		CRM(1)	0.293	4.08
	M1(2), R90(4), PTSE(1)	CTH(0)	0.114	4.08
		CTH(1)	0.969	4.08
		CRM(0)	0.043	4.08
		CRM(1)	0.434	4.08
UGNE:	M1/PGNE(5)	CTH(0-3)	1.228	2.61
		CTBBK(1,2)	4.556**	3.15
		CRM(1,2)	1.292	3.15
		CRM(0-2)	1.052	2.76
	M1/PGNE(5), PTSE(1)	CTH(0-3)	0.463	2.61
		CTBBK(1,2)	4.961**	3.23
		CRM(1,2)	0.873	3.23
		CRM(0-2)	0.570	2.84
PGNE:	M2(2)	CSTB(0)	2.254	4.00
		BSLN(0)	4.375*	4.00
		CC(1)	2.344	4.00
	FI-PHMS(4)	CSTB(0)	4.618*	4.00
		BSLN(0)	3.039	4.00
		CC(1)	2.142	4.00
	M2(2), R90(1), PTSE(1)	CSTB(0)	1.271	4.00
		BSLN(0)	2.021	4.00
		CC(1)	0.811	4.00
	FI-PHMS(4), UGNE(1)	CSTB(0)	3.297	4.00
		BSLN(0)	2.462	4.00
		CC(1)	0.449	4.00

* Significant at the 5 per cent level.
** Significant at the 1 per cent level.

For nominal spending, the M1(2) and multivariate M1 model forecasts are combined with forecasts from two credit models and a combined real spending and price forecast. The results in Table 14 indicate that the combined real income/price forecast which pairs the UGNE forecast from the consumer credit CIM with the consumer credit CC(1) bivariate model forecast for prices, is significant in regressions with the bivariate and multivariate monetary model forecasts. However, the M1 bivariate and multivariate forecasts are weighted much more heavily than the credit forecast.

The regressions for real spending reveal that forecasts from the credit models are significant when combined with the bivariate and multivariate M1/P model forecasts and the estimated coefficients on the credit model forecasts tend to be larger than those on the monetary model forecasts.

For the GNE price deflator, the credit model forecasts are all significant when paired with the forecasts from the FI-PHMS and M2 MIMs. The credit model forecasts are, however, less significant when combined with forecasts from the bivariate monetary models. The weights placed on the credit and monetary model forecasts are often (but not always) similar.

The results reported in this section suggest that credit measures add information to that provided by the monetary aggregates. The encompassing tests indicate that credit performs best, relative to and in conjunction with the monetary aggregates, in the real spending and price models. However, many of the credit forecasts are significant in regressions of actual values of the goal variables on monetary and credit model forecasts

Table 14:

COMBINED FORECASTS FROM MONETARY AND CREDIT INDICATOR MODELS (1975Q1-1986Q4)

Money model	Weight		Credit model	Weight		RMSE
YGNE:						
M1(2)	0.646	(3.418)	CTH(0)	0.316	(1.601)	0.803
	0.635	(3.191)	CTH(1), PTSE(1)	0.303	(1.570)	0.804
	0.545	(3.552)	CC(0-3) & CC(1)	0.400	(2.675)	0.767
M1(2), R90(4), PTSE(1)	0.682	(5.060)	CTH(0)	0.308	(2.248)	0.721
	0.829	(4.217)	CTH(1), PTSE(1)	0.138	(0.744)	0.755
	0.612	(5.284)	CC(0-3) & CC(1)	0.361	(3.283)	0.683
UGNE:						
M1/PGNE(5)	0.439	(3.162)	CTH(0-3)	0.407	(2.740)	0.838
	0.397	(2.702)	CC(0-3)	0.425	(2.824)	0.834
	0.226	(1.551)	CTBKK(1,2), PTSE(1)	0.478	(4.224)	0.767
M1/PGNE, PTSE(1)	0.355	(2.883)	CTH(0-3)	0.437	(2.931)	0.851
	0.320	(2.530)	CC(0-3)	0.459	(3.132)	0.841
	0.119	(0.862)	CTBKK(1,2), PTSE(1)	0.529	(4.338)	0.781
PGNE:						
FI-PHMS(4)	0.501	(2.579)	CSTB(0)	0.448	(2.238)	0.626
	0.423	(2.220)	BSLN(0)	0.524	(2.449)	0.620
	0.609	(3.328)	CC(0)	0.357	(1.768)	0.637
	0.627	(3.034)	CC(1)	0.329	(1.469)	0.644
M2(2)	0.523	(1.665)	CSTB(0)	0.436	(1.402)	0.650
	0.366	(1.235)	BSLN(0)	0.590	(2.025)	0.636
	0.742	(2.719)	CC(0)	0.232	(0.802)	0.659
	0.705	(2.643)	CC(1)	0.268	(0.963)	0.657
M2(2), R90(1) PTSE(1)	0.524	(2.880)	CSTB(0)	0.419	(2.204)	0.618
	0.461	(2.732)	BSLN(0)	0.485	(2.776)	0.600
	0.615	(3.663)	CC(0)	0.345	(1.836)	0.626
	0.587	(3.774)	CC(1)	0.374	(2.190)	0.617
FI-PHMS, UGNE(1)	0.347	(1.706)	CSTB(0)	0.609	(2.971)	0.649
	0.252	(1.198)	BSLN(0)	0.699	(3.316)	0.637
	0.478	(2.190)	CC(0)	0.505	(2.143)	0.675
	0.461	(2.111)	CC(1)	0.515	(2.222)	0.673

Note:
Bracketed numbers are t-statistics.

for these variables.[26] While the majority of the significant credit forecasts are derived from models which include (and often include only) contemporaneous credit, there are several lagged credit models (for example, the total household credit MIM for nominal spending and the consumer credit BIM for prices) which generate forecasts that add significant information to the forecasts obtained from the monetary models. Thus we find many instances where contemporaneous credit - and in some instances, lagged credit - adds significant information to the indicator models based upon the monetary aggregates.

6 CONCLUSIONS

Throughout this paper, the credit aggregates have been subjected to a barrage of empirical tests which permit us to define the role of credit as an indicator of nominal spending and of its real and price components. Two basic questions are addressed by the methodology: (i) Which credit aggregates contain the most information about nominal and real income and prices? and (ii) How does the information content of credit compare with the information content of money? The answers to these questions can be used to determine if and where a niche exists for credit in the set of macroeconomic indicators.

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26. This technique was repeated using "static" forecasts from models estimated over the 71Q1-85Q4 period. (The qualifier "static" refers to the fact that the model parameters are not updated prior to each quarterly forecast.) As for the recursive forecasts (reported above), almost all the static credit forecasts add information to the money model forecasts. Hence the significance of the credit forecasts is not due to the recursive estimation of the models. Initially, this result was perceived as somewhat surprising given the correspondence between this test and the J-test and earlier encompassing tests which found little significant additional credit information. This test (combining static forecasts) differs from the J-test in that: (i) the J-test restricts the sum of the weights on the forecasts to one; (ii) the J-tests were applied over the 71Q1-85Q4 sample period, while the forecast regressions are run over the 75Q4-86Q4 period; and (iii) the weights on the forecasts and coefficients on the explanatory variables in the monetary model are estimated simultaneously for the J-test, while the forecast regressions apply a two-step procedure in which each of the models is estimated separately and then the weights on each forecast are estimated. (The encompassing test estimates coefficients on credit and money simultaneously.) The J-tests and forecast regressions were repeated for the 75Q1-85Q4 period with essentially no change on either set of results. This suggests that the simultaneous estimation of forecast weights and parameters of the monetary model is responsible for the difference in the J-test (and initial encompassing test) and combined forecast regression results.

The first question requires isolation of a parsimonious set of the most informative credit aggregates. For nominal spending, contemporaneous total household credit is most informative. For prices, again contemporaneous credit captures most of the information content in credit, but it is the business credit aggregates - business loans at chartered banks and short-term business credit - which perform best. Only for real spending do we find significant leading information in credit. Both residential mortgage credit and the chartered bank total business credit aggregates tend to be informative about real GNE. (There is, however, some question of the stability of the relationship between the chartered bank aggregate and real income, limiting the usefulness of this model.)

Comparison of the performances of the monetary and credit aggregates reveals that M1 and M2 are consistently better indicators than the best credit aggregates. On the basis of simple economic theory, it is not clear why the monetary aggregates tend to dominate the credit aggregates in this context. Two potential explanations can be posited: (i) the aggregation assumptions used for the monetary aggregates are more "economically" sensible than the rules used to aggregate various components of the credit measures and/or (ii) credit may indeed be passive, following movements in money, prices and income, at least in the context of quarterly data. Theories such as the buffer stock may describe monthly or even weekly dynamics in money and credit but are lost in data of lower frequency.

Does a niche exist, then, for credit, in our set of macroeconomic indicators? The answer is a mild yes, but credit is not expected to assume a dominant role. The significance of credit in the real income models built from the monetary aggregates clearly indicates that credit is informative in this context. The results are somewhat less favourable for credit in the nominal income and price models, especially as it is contemporaneous credit which appears to contain most of the relevant information. Nevertheless, for all three goal variables, forecasts from the credit models appear to add significant information to the forecasts

from the monetary models. Thus the credit models can be used to check and improve the forecasts obtained from the indicator models constructed from the monetary aggregates.

The future of credit aggregates as macroeconomic indicators should also be evaluated from a more theoretical perspective. The arguments posited above to explain the relative strength of the monetary aggregates suggest that the full potential of credit may yet be discovered. First, the nature of the aggregation assumptions used for credit suggest that the links between these aggregates and the components of total spending should be investigated. Intuitively, it seems likely that there is sectoral information in the different credit aggregates. Secondly, the periodicity of the data used in this study may mask any lead/lag relationship between assets and liabilities. Hence it is possible that monthly indicator models will find more additional information in credit.

It is certain that the timing and linkages between movements in money, credit and the rest of the macroeconomy are complex, and the true nature of these relationships can only be discovered in the context of a fully articulated structural model. Perhaps it is in that context only that credit will be given its due.

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